Temporal Case-Based Reasoning for Reservoir Spillway Gate Operation Recommendation

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***Abstract*-In the traditional decision making process, in order to solve a problem, every possible solution will be generated and evaluated. The most optimum decision will be selected. However, this approach is unsuitable for urgent decision making, due to the time needed to evaluate all option. This project propose Temporal Case Based Reasoning (TCBR) technique to support dam technician in deciding which reservoir spillway gate will be opened or closed to release excess water in order to maintain a safe water level. Previous hydrological data of Timah Tasoh Dam, State of Perlis, Malaysia were used to develop the gate operation decision support model, which covers reservoir spillway gate operation activities from year 1998 to 2004. This model was then tested, and yielded up to 89 percent decision accuracy.**

I. Introduction

In an emergency situation, timeliness and accuracy of decision is vital. Decision error will result catastrophic event that can jeopardize the public safety and properties. For a reservoir, critical element of the safety is the decision either to open or close the reservoir spillway gate. The decision failures could risk the downstream population surrounding the dam area to flood. In this research, the main objective is to classify when the reservoir gate need to be open to release excess water hence maintaining the reservoir at a safe level.

The problem faced by the dams is the unexpected sediment or silt below the dam that cause loosing their total water capacity. Timah Tasoh Dam can store 40 million cubic meters at the normal pool of 29.1 meter when it begins operation in 1992. After 14 years of operation, the current total storage capacity in Timah Tasuh Dam is less then 40 million cubic meters at the normal pool. Due to this reason, the reservoir gate operation guideline used 14 years ago needs to adapt to this new situation.

Due to the sediment deposition problem, the dam engineer has to manually calculate the rainfall and water level at the dam before they can make a decision either to open or close the gate. Any miscalculated decision by the dam engineer could cause loss of human life and property damages.

Other problem face is the expert turns around due to promotion to a new position, or being transferred to a new place. They will bring their experience and expertise as well. The new dam engineer needs to learn the skill to develop his experience. This skill takes a long time to develop. In computer science, these kinds of problem solving algorithm that imitate how the expert solve the problem via past experience are call Case-Based Reasoning (CBR) technique. In this technique new problem are solve by recalling from previous solve problem which are stored in the case-based.

In this research, hydrology data are in time series or temporal representation. The CBR engine for temporal data was designed that can support temporal data mining. A prototype was developed adopting the CBR engine where the temporal hydrology data are used to evaluate the decision recommended given by the prototype versus the expert.

II. Case Based Reasoning (CBR)

Case-Based Reasoning is an Artificial Intelligence (AI) technique that imitates how human make the decision. In CBR, new problem are solve by recalling from previous solved problem which are store in the case-base [1].

CBR imitate human thought process, and performs its own cycle. The CBR cycle start when the new problem occurs. CBR engine will find or retrieve the matched cases in the case-base for the new problem. The solution of the most similar cases will be reused as the propose solution to the new problem. If the solution need to be modified, adaptation from the propose solution have to be made before suggesting the final solution to the user. If the problem is solved, the new case will be retained to the case-base for future reference. Fig. 1 shows the overall CBR cycle adopted from [1].

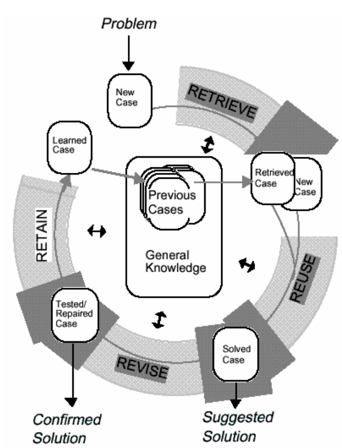

Fig. 1. The CBR cycle [1].

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At the reservoir, dam engineer used their experience or knowledge to make the decision either to open or close the reservoir gate. This kind of approach is similar with the CBR that used previous knowledge or cases to solve new problem.

Generally, CBR can be used in the various domains, such as medical, facial expression, computer networks and engineering [2] [3] [4] [5] that also used past experience to make decision.

III. Proposed Temporal Case-Based Reasoning Engine.

The propose model consist of three main module. These modules are: Database and Data Preparation Module, Temporal Case-Based Reasoning Modules and Decision Support Module. The detail of those modules will be explained in the following section. Fig. 2 shows the design of each module.

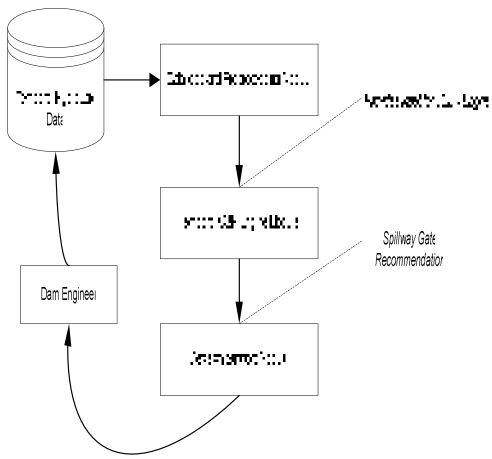

Fig. 2. The proposed TCBR model.

The input pattern for this model is gathered from temporal hydrology data that was taken from Timah Tasuh Dam at Perlis, Malaysia. A prototype was developed using the model proposed and is written using Visual Basic 6.0 programming language that run under the Windows platform.

A. Database and Data Preparation Module

The function of Database and Data Preparation Module is to provide the select a quality and suitable input for the Temporal Case-Based Reasoning Module. According to [6] learning system requires data preprocessing before classification. Failing to do so, will lead to classification error that will affect the data mining process. Fig. 3 shows the preprocessing process.

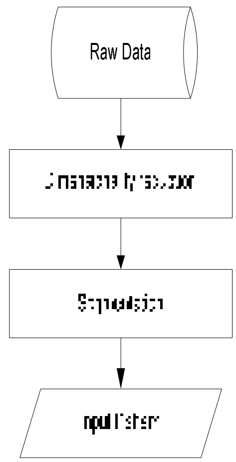

Fig. 3. Preprocessing process.

The data from Hydrology Unit, Drainage and Irrigation Department, State of Perlis, specifically the Timah Tasuh Dam operation has many attributes where only a few was chosen as the determinant for the decision to open the reservoir spillway gate. From the interview with the dam engineer, they need to use several attributes only to make the decision either to open the gate or not. The data mining process follows the expert heuristic in their decision making. Attribute chosen were determined from the dimensionality reduction process.

After the dimensionality reduction process, segmentation of the data needs to be done. With segmentation, the data is partitioned into disjointed groupings of similar tuples [7].

In this module, since the hydrology data is temporal data with the time delayed event, sliding windows technique was propose as the segmentation technique for collecting temporal pattern for classification [8]. Fig. 4 shows the pseudo-code for the sliding window where n is the size of the window. In this study n is taken as the value of 2 based on a similar study [8].

for time t **to** end of file
  read data at time t
  get data at $(t-1)\ldots.(t-n)$
  add into window slices set
next

Fig. 4. Steps for sliding window

The event of gate opening depends on the reservoir water level that rises due to rainfall. The rainfall is the cause and there is a time delay between the rainfall and the consequence effect to the water level. Thus the window is use to capture this delay. The windowing is a continuous process that will scan all the temporal data to segment and partitioned it into group. The partitioned data will be the input pattern for the temporal case-based reasoning engine module.

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B. Temporal Case-Based Reasoning Engine Module

The Temporal Case-Based Reasoning (TCBR) engine module is the core module in the model. It utilizes the state-of-the-art of the AI technique to imitate human intelligence in decision-making. The modules consist of two main components, which are case acquisition and testing (new case). In this module, the CBR engines are develop to work in the temporal environment. Fig. 4 shows the proposed TCBR engine.

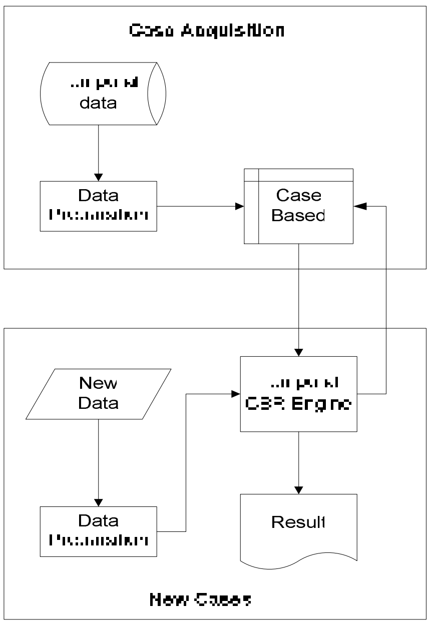

Fig. 4. The proposed TCBR engine.

Block-City (Manhattan) distance measure was used for the calculating the similarities in the TCBR engine. CBR systems use global similarity measures to provide acceptable case-matching behavior. The formula for block-city similarities calculation is given in (1).

$$\frac{\sum_{i=1}^{n} w_i sim(f_i^N, f_i^O)}{\sum_{i=1}^{n} w_i} \qquad (1)$$

where w and, *sim* are the measured weighting values, and local similarity function.

C. Decision Support Module

The decision support module allows the dam engineer to have access to the TCBR engine module output. In this module, the result from TCBR engine will be extracted and presented to the user as shown in Fig. 5.

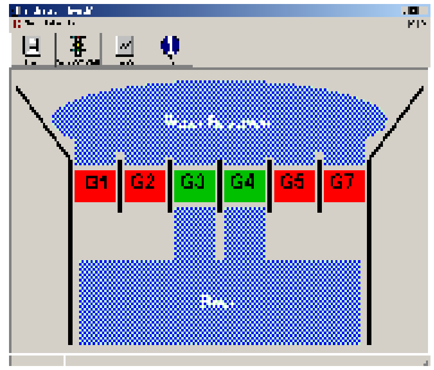

Fig. 5. Decision support module user interface.

The result from the model will provide guidance for dam engineer to support their decision either to open the spillway gate or not. With this model, dam engineer does not need to manually calculate for the decision either to open or close the spillway gate. This model assists decision-making and also reduces human error in the decision making that can jeopardize the human life and property at the downstream area.

IV. Result

In this section, the performance evaluation of the TCBR spillway gate operation model will be discussed. The TBCR model was implemented using the Visual Basic version. 6.0. The experiments were carried out under the Windows 2000 platform using 800-megaherz Pentium III processor and 256 MB RAM.

The performance evaluation was carried with daily hydrology data of Timah Tasoh Dam. The data range form year 1998 to 2004. Water level and rainfall measurement from six telemetry stations around the dam were used as the input pattern for the TCBR model. The original data was stored in MS-Excel and converted to text file (**.txt*) as the input pattern. All data were in the temporal sequence. Table 1 and 2 show the representation for the water level and rainfall use at Timah Tasoh Dam according to the domain expert classification.

TABLE I
WATER LEVEL STAGE REPRESENTATION

Water Level (m)	Flood Stage
< 29.0	Normal
< 29.4	Alert
< 29.6	Warning
> 29.6	Danger

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TABLE 2
RAINFALL CATEGORY REPRESENTATION

Rainfall (mm)	Category
0	None
1 – 10	Light
11 – 30	Moderate
31 – 60	Heavy
> 60	Very Heavy

The parameters for the performance measurement of this TCBR model were adopted from [9]. The parameters used are t_p, f_p, t_n and f_n as explained in Table 3.

TABLE 3
PARAMETERS USE FOR THE PERFORMANCE MEASUREMENT

Measurement	Meaning
t_p	True positive. Number of event correctly predicted
f_p	False positive. Number of predicted event but in actual non-event
t_n	True negative. Number of non-event correctly predicted
f_n	False negative. Number of predicted non-event but an actual event
Sensitivity (Sen)	The accuracy of correctly predicted event $= \frac{t_p}{t_p + f_n}$
Specificity (Spec)	The accuracy of correctly predicted non-event $= \frac{t_n}{t_n + f_p}$
Total Accuracy (Acc)	The ratio of total correct prediction $= \frac{t_p + t_n}{t_n + f_n + t_p + f_p}$

Data from 1998 to 2003 operation was use as the training data and year 2004 for testing. Decision predicted for the daily spillway gate operation in year 2004 compared to the actual decision made by the expert was found of 89.6 % of total accuracy. The result also shows the model has obtain 89.5 % of specificity and 100 % of sensitivity.

V. CONCLUSION

This study proposed a case based reasoning technique used in a temporal data application for decision recommendation based on historical data. Sliding window was use as the segmentation technique that is able to capture the temporal pattern including the time delay. Each window was treated as a unique case. The proposed model performance was comparable to the actual decision with about 11% false alarm. Future work will enhance the TCBR engine such that it can reduce the false alarm rate.

ACKNOWLEDGMENT

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